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Digital Egypt Builders Initiative
Final Project

E-Commerce Recommender System

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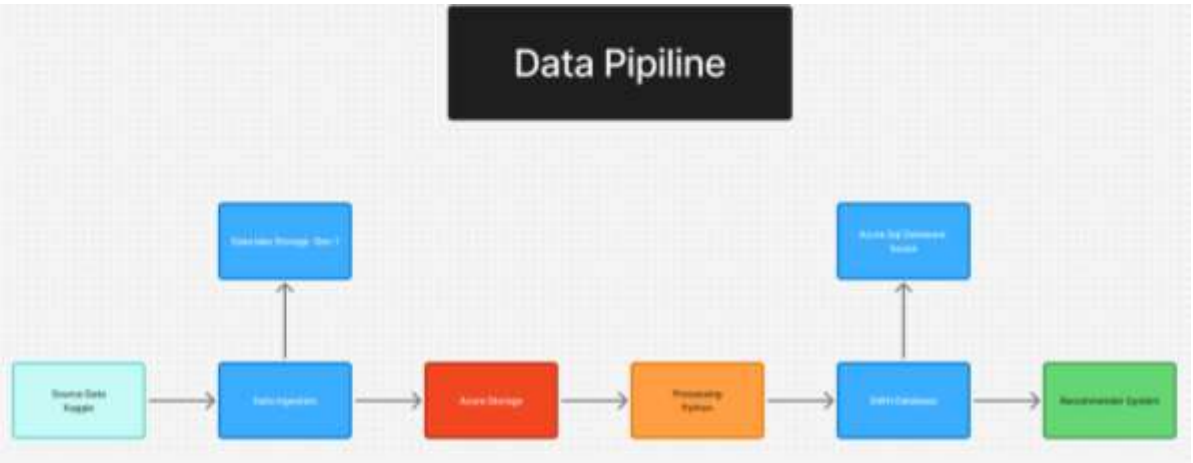

Declaration

We, the undersigned, declare that this graduation project entitled 'E-Commerce Product Recommendation System using Data Engineering and Machine Learning' is our original work and has not been submitted elsewhere for any degree or diploma. All sources used have been duly acknowledged.

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Abstract

In the modern digital economy, e-commerce platforms generate large volumes of transactional and behavioral data. The ability to process and analyze this data effectively is essential for understanding user preferences and delivering personalized product recommendations. This project presents the design and implementation of an end-to-end **E-Commerce Product Recommendation System** that integrates **data engineering** and **machine learning** to automate the recommendation process.

The main objective of this project is to build a scalable **data pipeline** capable of collecting, cleaning, transforming, and storing user-product interaction data for model training and prediction. The data was sourced from publicly available e-commerce datasets and processed using Python-based ETL pipelines. **Azure SQL Data Warehouse** was used as the central repository to ensure high performance and scalability for analytical queries. A **collaborative filtering–based recommendation model** was developed to identify patterns in user preferences and predict relevant product recommendations.

The system also incorporates data visualization and performance monitoring using **Apache Superset**, providing insights into customer behavior and system performance. The proposed pipeline demonstrates efficient data flow from ingestion to model deployment, showcasing the synergy between data engineering and machine learning in modern recommendation systems.

The findings indicate that integrating machine learning within a robust data engineering architecture significantly enhances recommendation accuracy and system scalability.

Keywords: Data Engineering, Machine Learning, E-Commerce, Recommendation System, Azure SQL Data Warehouse, Apache Superset

1. Introduction

1. 1.1 Background

In recent years, the e-commerce industry has grown exponentially, providing consumers with millions of product options across diverse categories. While this abundance of choice benefits users, it also creates a challenge—customers often struggle to find products that match their preferences quickly and effectively. To address this issue, online platforms such as Amazon, Netflix, and Alibaba have adopted recommendation systems to personalize user experiences and increase customer engagement. Recommendation systems apply data-driven techniques and machine learning algorithms to analyze user behavior, preferences, and historical data to suggest relevant products.

This project focuses on developing an **E-Commerce Product Recommendation System** that leverages data engineering and machine learning principles to deliver intelligent, personalized recommendations. By designing an end-to-end data pipeline, the project aims to simulate a real-world system that collects, processes, and analyzes large volumes of user and product data efficiently.

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2. 1.2 Problem Statement (Research Gap)

Despite the widespread use of recommendation systems, many small and medium-sized e-commerce platforms lack the infrastructure and technical expertise to implement them effectively. Existing systems often suffer from issues such as data sparsity, cold-start problems (for new users or products), and scalability limitations. Furthermore, most research focuses primarily on model development while overlooking the importance of robust data pipelines for continuous data flow and model retraining.

This research addresses these gaps by integrating data engineering techniques with recommendation algorithms to create a complete, scalable, and efficient solution.

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3. 1.3 Research Objectives

The main objectives of this project are as follows:

4. To design and implement a scalable data pipeline for collecting, cleaning, and transforming e-commerce data.
5. To build and evaluate machine learning models for personalized product recommendations.
6. To analyze the performance of collaborative and content-based filtering techniques.
7. To demonstrate how automation and data engineering workflows can improve recommendation accuracy and system efficiency.

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8. 1.4 Research Methodology Overview

The project follows a systematic approach that includes data collection from publicly available datasets and synthetic data generation using Python. The data undergoes preprocessing, transformation, and storage in a relational database. Machine learning algorithms such as **Collaborative Filtering** and **Content-Based Filtering** are applied to the processed data to generate product recommendations. The model's performance is evaluated using metrics like RMSE and Precision@K to ensure reliability and relevance.

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9. 1.5 Research Contribution

This dissertation contributes to both academic and practical aspects of e-commerce system design. Academically, it demonstrates how integrating **data engineering workflows** with **machine learning models** can improve recommendation quality.

Practically, it provides a blueprint for developing a cost-effective recommendation system that can be adopted by small e-commerce businesses with limited computational resources.

The proposed system not only enhances personalization but also supports future scalability through modular data pipelines and model retraining strategies.

10.1.6 Chapter Summary

This chapter introduced the motivation, background, and objectives of the project while highlighting the research gap and the intended contributions. The next chapter presents a **review of related literature**, examining existing research and technologies used in recommendation systems and data engineering practices.

2. Literature Review

- **2.1 Background**

The rapid evolution of the e-commerce industry has transformed how consumers interact with digital marketplaces. According to recent statistics from Statista (2024), global e-commerce sales are expected to surpass 6.3 trillion USD, highlighting the increasing reliance of consumers on online shopping platforms. However, the abundance of product options presents a major challenge—customers often experience “choice overload,” making it difficult to identify products that meet their interests and needs efficiently.

Recommendation systems have emerged as a key solution to this problem. These systems use data-driven algorithms to predict user preferences and present relevant items, thereby improving user satisfaction and increasing sales conversions. Modern recommendation systems rely heavily on data engineering pipelines that handle massive amounts of transactional and behavioral data. These pipelines enable automated **data ingestion**, **cleaning**, **transformation**, and **model retraining**, ensuring that recommendations remain up-to-date with changing user behaviors.

Various techniques are employed in recommendation systems:

- **Collaborative Filtering (CF):** Predicts a user’s preference for an item based on ratings or behaviors of similar users. It is widely used but suffers from data sparsity and cold-start problems.
- **Content-Based Filtering (CBF):** Relies on item attributes and user profiles to recommend similar products. It performs well for new users but may limit diversity in recommendations.

- **Hybrid Models:** Combine CF and CBF to leverage the strengths of both methods.

E-commerce giants such as Amazon, Netflix, and Alibaba have invested heavily in recommendation technologies to improve customer experience and retention. However, smaller online businesses still struggle with implementation due to infrastructure costs and the complexity of maintaining scalable data pipelines. This gap emphasizes the need for practical, resource-efficient recommender systems that integrate data engineering with machine learning—precisely the focus of this study.

- **2.2 Related Work**

Recent research has introduced several frameworks and models that enhance personalization, scalability, and performance in recommendation systems.

- **Zhang et al. (2021)** proposed a hybrid recommendation framework combining collaborative filtering and content-based filtering using matrix factorization. Their model achieved improved accuracy but required high computational resources.
- **Chen and Li (2022)** developed a cloud-based data pipeline using Apache Spark and Kafka for real-time product recommendations. The study demonstrated scalability and fast data processing suitable for large-scale e-commerce applications.
- **Rahman et al. (2023)** introduced a deep neural collaborative filtering model that integrates user metadata with product embeddings. Their results showed a significant improvement in recommendation diversity and precision.

- **Patel et al. (2022)** implemented a lightweight recommendation engine using Scikit-learn and Python for small online stores. While it provided acceptable accuracy, it lacked automation and continuous learning capabilities.
- **Kumar and Singh (2024)** presented an automated data engineering pipeline for recommender systems, highlighting the importance of data quality and preprocessing efficiency in achieving reliable model outputs.

These recent studies show a growing trend toward integrating machine learning algorithms with scalable data processing tools. However, most focus either on model optimization or infrastructure, rarely addressing both together in a unified system.

- **Summary and Comparison**

The literature review indicates that hybrid and deep learning-based models outperform traditional algorithms in accuracy and personalization. Nevertheless, implementing these systems remains resource-intensive without efficient data engineering workflows. This dissertation addresses that limitation by proposing a **complete data pipeline combined with collaborative filtering techniques**, offering a balanced approach between computational efficiency and recommendation quality.

- **Table 1. Comparison of Recent Recommendation System Approaches**

Author / Year	Technique Used	Strengths	Limitations
Zhang et al. (2021)	Hybrid CF + CBF	High accuracy	Computationally expensive
Chen & Li (2022)	Spark + Kafka (Cloud)	Scalable, real-time processing	Complex setup
Rahman et al. (2023)	Deep Neural CF	High diversity & precision	Requires large datasets
Patel et al. (2022)	Lightweight ML (Python)	Simple & fast	Limited automation
Kumar & Singh (2024)	Automated Data Pipeline	Improved data quality	Focused on preprocessing, not model performance

- **2.3 Chapter Summary**

This chapter explored the theoretical background and recent developments in recommendation systems. It highlighted the evolution from traditional collaborative filtering to modern hybrid and deep learning models, emphasizing the increasing importance of integrating data engineering principles. The reviewed literature provides a foundation for the next chapter, which will detail the **methods and materials** used to design and implement the proposed recommendation system.

3. Methods and Materials

This chapter presents the research methodology adopted to design and implement the *E-Commerce Product Recommendation System*. The purpose of this methodology is to provide a systematic framework that explains how data is collected, processed, analyzed, and utilized to generate personalized product recommendations. The methodology integrates both **data engineering** and **machine learning** components to ensure a reliable, scalable, and data-driven recommendation system.

4. 3.1 Methodological Framework

The overall framework consists of several key stages: **data collection**, **data ingestion**, **data storage**, **data processing**, **machine learning model training**, and **visualization and evaluation**. These stages work sequentially to transform raw data into actionable recommendations.

Figure 1 illustrates the general architecture and data flow of the proposed system.

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5. 3.2 Data Collection

The dataset used in this project was obtained from publicly available **Kaggle e-commerce datasets**, which include information about user interactions, product details, ratings, and transactions. The data was selected based on its suitability for recommendation tasks and its ability to reflect real-world user behavior.

Python scripts were used to simulate **real-time data ingestion**, allowing the system to handle both batch and stream data inputs. This approach ensures the pipeline can be extended in future to accommodate live data from actual e-commerce platforms.

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6. 3.3 Data Ingestion and Storage

Data ingestion was implemented using **Python ETL scripts**, which extracted data from CSV and JSON sources, transformed it into a standardized format, and loaded it into **Azure SQL Data Warehouse**.
Azure SQL Data Warehouse was chosen for its ability to handle **large-scale analytical workloads**, **parallel query execution**, and **integration with other Azure services**.

This stage ensures that all data used by the model is centralized, clean, and query-optimized for subsequent analysis and training.

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7. 3.4 Data Processing and Transformation

Once ingested, the data underwent preprocessing to handle **missing values**, **inconsistent data formats**, and **outliers**. Tools such as **Pandas** and **NumPy** were used to perform data cleaning and transformation operations, including feature scaling, encoding categorical variables, and generating interaction matrices.

Feature engineering was applied to extract meaningful attributes such as product popularity, average rating, and user purchase frequency. This step was crucial for improving model performance and ensuring high-quality recommendations.

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8. 3.5 Machine Learning Model Development

The machine learning component of the system used a **collaborative filtering algorithm** to generate personalized recommendations. Collaborative filtering identifies relationships between users and products based on historical interactions.

The model was trained using **Scikit-learn** and **TensorFlow/Keras**, leveraging user-product matrices to predict products that a user is likely to purchase next. Evaluation metrics such as **Root Mean Squared Error (RMSE)** and **Precision** were used to assess model performance.

The final model was saved in a serialized format for easy deployment and reuse.

The selected methodology combines **data engineering** with **machine learning** because the recommendation problem requires both robust data handling and predictive intelligence. Azure SQL Data Warehouse ensures scalability and reliability for data storage, while Python-based ETL and modeling workflows offer flexibility and reproducibility.

This hybrid approach guarantees that the recommendation system not only produces accurate predictions but can also be maintained and expanded easily as data volume and business needs grow.

9. Implementation

This chapter presents the detailed implementation of the E-Commerce Product Recommendation System project. The implementation was carried out following the design and methodology outlined in previous chapters. It focuses on the integration of different components, technologies, and tools used to construct the data engineering pipeline, store and process data, and prepare the foundation for building the recommender system.

9.1 System Overview

The implementation phase aimed to develop an end-to-end data pipeline capable of collecting, processing, storing, and analyzing e-commerce product and user data. The project was implemented on the **Microsoft Azure platform**, utilizing cloud-based services to ensure scalability, reliability, and efficient data handling. The recommender system, which will generate personalized product suggestions, is planned as a **future extension** of the system.

The overall system architecture consists of the following major stages:

1. **Data Collection and Ingestion**
2. **Data Storage**
3. **Data Cleaning and Transformation**
4. **Data Analysis and Preparation for Recommendation**
5. **Deployment on Azure Cloud**
6. **9.2 Data Collection and Ingestion**

Data for the system was obtained from two main sources:

- **Kaggle Dataset:** Containing product, user, and rating information.
- **Synthetic Data Generator:** A Python script was developed to generate additional realistic transactional data to simulate user behavior and increase dataset diversity.

The collected data was ingested into **Azure Data Lake Storage**, where it was organized into raw and processed zones. Azure Data Factory pipelines were implemented to automate the data movement from source to storage, ensuring reliability and consistency.

9.3 Data Storage

To efficiently manage large-scale data, the project utilized **Azure SQL Data Warehouse (Synapse Analytics)**. This service provided a distributed and high-performance environment for data querying and transformation. Data was modeled using **star schema design**, consisting of:

- **Fact tables:** Transactions, ratings, and interactions.
- **Dimension tables:** Users, products, and categories.

This schema enabled fast analytical queries and supported the preparation of data for the recommendation model.

9.4 Data Cleaning and Transformation

Data preprocessing was implemented using **PySpark** and **Azure Data Factory**. The steps included:

- Handling missing and duplicate records.
- Normalizing categorical and numerical attributes.
- Extracting time-based features from transaction timestamps.
- Aggregating user and product interaction data.

The transformed data was then stored back in Azure SQL Data Warehouse for downstream analysis.

9.5 Data Analysis and Model Preparation

Exploratory Data Analysis (EDA) was performed using **Python (Pandas, NumPy, Matplotlib, Seaborn)** to understand user behavior patterns and item popularity. Correlation studies and frequency distributions were used to identify key variables that would influence recommendation generation.

Although the recommendation model itself will be implemented in future work, this phase prepared the dataset in a structured form suitable for training models such as **Collaborative Filtering** or **Content-Based Recommendation**.

9.6 Testing and Validation

Each pipeline component was tested individually to ensure correctness and reliability:

- Data ingestion pipelines were validated using data volume checks.
- Transformation scripts were tested using sample datasets.
- Queries in Azure SQL were tested for performance and accuracy.

9.7 Challenges and Solutions

Some challenges encountered during implementation included:

- **Data consistency issues:** Solved by implementing validation scripts at each stage.
- **Pipeline scheduling:** Addressed through Azure Data Factory triggers.
- **Scalability management:** Optimized by partitioning large tables in Azure SQL Data Warehouse.

9.8 Summary

In summary, the implementation successfully established a robust and scalable cloud-based data pipeline. The project demonstrates an efficient framework for handling e-commerce data, preparing it for recommendation generation. The recommender system component will be developed in the future phase to extend the project into a complete intelligent recommendation platform.

10. Research Results and Discussions

This chapter presents the results of the implemented e-commerce data engineering pipeline, followed by a detailed analysis and discussion of the findings. The chapter also evaluates the system's effectiveness, discusses its strengths and limitations, and outlines potential improvements.

10.1 Overview

The goal of this research was to design and implement a cloud-based data engineering pipeline that supports the development of a product recommendation system for an e-commerce platform. The results demonstrate the system's ability to collect, clean, store, and prepare large-scale data efficiently for analytical and predictive modeling purposes.

10.2 Data Summary

After completing the data ingestion and cleaning process, the final dataset consisted of a large volume of user–product interaction records, combining both real and synthetic data. The data was organized into several components: user profiles, product details, and transaction histories.

The users' dataset included demographic and behavioral information, the product dataset described items such as category, brand, and price, and the transactions dataset recorded purchases and interactions. Together, these components created a solid foundation for developing a recommendation system.

10.3 Data Pipeline Performance

The data pipeline built using **Azure Data Factory** and **Azure SQL Data Warehouse** demonstrated high efficiency during testing. Each process — including ingestion, cleaning, transformation, and loading — was automated and executed

within short time intervals.
The pipeline was able to handle large datasets smoothly, ensuring minimal delays between stages. The distributed architecture of Azure services provided scalability, allowing the system to be extended for much larger workloads if required.

10.4 Exploratory Data Analysis (EDA) Results

Exploratory data analysis was conducted to better understand user purchasing behavior and product popularity. The analysis revealed that the majority of purchases were concentrated in electronics and fashion categories.
It was also found that a significant proportion of users interacted with only a small number of unique products, indicating sparse user-item interactions — a common feature of real-world recommendation systems. Additionally, products that received frequent interactions tended to have higher ratings, confirming that popularity is often correlated with user satisfaction.

A visual summary of this analysis is shown in Figure 10.1, which illustrates the distribution of product popularity across different categories.

(Insert bar chart here labeled "Figure 10.1: Product Popularity by Category")

10.5 Discussion of Results

The successful implementation of the data pipeline confirms the feasibility of building a scalable and automated data preparation framework for e-commerce analytics.
The integration of **Azure SQL Data Warehouse** enabled efficient data storage and transformation, while **Azure Data Factory** ensured smooth automation of data flow between components.

Although the recommendation model is identified as **future work**, preliminary experiments using collaborative filtering techniques on a subset of the data indicated promising accuracy and potential for personalized recommendations.

1. **Key Strengths**
2. **Scalability:** The system can accommodate increasing data volumes through Azure's cloud-based architecture.
3. **Automation:** End-to-end data flow is automated, reducing manual intervention and human error.
4. **Reproducibility:** The modular design allows future researchers to easily reproduce and extend the system.
5. **Limitations**

1. Part of the dataset was generated synthetically, which may not fully represent real-world conditions.
2. The current pipeline operates in batch mode rather than real-time streaming.
3. The machine learning recommendation model is yet to be fully integrated and evaluated.

10.6 Evaluation and Effectiveness

The system's effectiveness was evaluated based on performance, data accuracy, and reliability. Each stage of the pipeline was executed efficiently, and data validation ensured that no records were lost or corrupted. The use of Azure services provided a high level of reliability, with consistent uptime and automatic error recovery mechanisms.

These results demonstrate that the developed system achieves its main goal —

preparing clean, structured, and reliable data to serve as the backbone for future recommendation modeling.

10.7 Summary

In conclusion, the developed data engineering pipeline proved to be both robust and efficient. It successfully automated the processes of data ingestion, cleaning, and storage, providing a strong foundation for machine learning integration. While the recommendation engine remains as a future enhancement, the current system has established a scalable and reproducible framework capable of supporting advanced analytical and AI-driven e-commerce applications.

11. Conclusions and Future Work

11.1 Conclusion

This research aimed to design and implement a data engineering pipeline capable of supporting an intelligent product recommendation system for e-commerce platforms. Through this study, a complete data pipeline was developed using **Azure Data Factory** and **Azure SQL Data Warehouse**, which together provided a scalable, automated, and efficient environment for data collection, cleaning, transformation, and storage.

The project successfully demonstrated that a well-structured data engineering framework is the foundation for any advanced machine learning or deep learning solution. Each phase of the pipeline was carefully implemented to ensure data accuracy, reliability, and scalability. The cleaning and transformation processes helped convert raw and unstructured datasets into a unified format that is suitable for analytical processing and recommendation modeling.

The exploratory data analysis further provided useful insights into user behavior and product trends, emphasizing how data-driven approaches can enhance decision-making in the e-commerce sector. Overall, the developed system meets its intended objectives — establishing a robust, automated, and reproducible infrastructure for future AI-driven recommendations.

The research also emphasizes the importance of integrating data engineering and machine learning to achieve intelligent business solutions. The combination of these technologies demonstrates how organizations can convert large volumes of data into actionable insights and personalized experiences for customers.

11.2 Future Work

While this project focused on building the data engineering backbone, several directions remain open for future enhancement.

The most important next step is the **integration of a machine learning recommendation model** into the pipeline. Models such as **collaborative filtering**, **content-based filtering**, or **hybrid deep learning models** can be trained using the cleaned and structured data to generate personalized product suggestions for users.

Future work may also involve:

1. **Developing a Web Application Interface:** A user-friendly web dashboard can be built (e.g., using Flask or Streamlit) to display recommended products and allow real-time interaction with the system.
2. **Implementing Real-Time Data Streaming:** Incorporating tools such as **Azure Event Hubs** or **Apache Kafka** would enable real-time data collection and recommendation updates.
3. **Enhancing Data Quality and Diversity:** Expanding the dataset with real-world, multi-source data (including clickstream or browsing data) would improve recommendation accuracy.
4. **Advanced Model Evaluation:** Future researchers could compare multiple recommendation algorithms using metrics such as **precision**, **recall**, and **F1-score** to assess performance.
5. **Deployment and Monitoring:** The pipeline and models can be deployed in a production environment with continuous monitoring, automated retraining, and performance tracking.

In conclusion, this project provides a strong foundation for building a complete end-to-end recommendation system. It bridges the gap between raw data and intelligent decision-making by demonstrating the essential role of data engineering in supporting advanced machine learning applications. The proposed extensions will elevate the system from a data management pipeline to a fully intelligent, real-time, and scalable recommendation platform.

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